

Optimal heliostat aiming strategy for uniform distribution of heat flux on the receiver of a solar power tower plant



Saeb M. Besarati, D. Yogi Goswami*, Elias K. Stefanakos

Clean Energy Research Center, University of South Florida, 4202 E. Fowler Av. ENB 118, Tampa, FL 33620, United States

ARTICLE INFO

Article history:

Received 30 December 2013

Accepted 10 April 2014

Available online 4 May 2014

Keywords:

Flux distribution

Solar power tower

Optimization

Genetic algorithm

ABSTRACT

Temperature distribution on the receiver surface of a solar power tower plant is of great importance. High temperature gradients may lead to local hot spots and consequently failure of the receiver. The temperature distribution can be controlled by defining several aiming points on the receiver surface and adjusting the heliostats accordingly. In this paper, a new optimization algorithm which works based on the principles of genetic algorithm is developed to find the optimal flux distribution on the receiver surface. The objective is to minimize the standard deviation of the flux density distribution by changing the aiming points of individual heliostats. Flux distribution of each heliostat is found by using the HFLCAL model [1], which is validated against experimental data. The results show that after employing the new algorithm the maximum flux density is reduced by an order of magnitude. The effects of number of aiming points and size of the aiming surface on the flux density distribution are investigated in detail.

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

In a solar power tower plant, the receiver plays an important role of intercepting reflected solar radiation from the heliostat field and transferring thermal energy to the heat transfer fluid. The main challenge associated with this process is the high temperature gradient at the receiver surface which may lead to local hot spots, and consequently, degradation and failure of the receiver [2]. The temperature distribution on the receiver surface depends on the design of the receiver, thermophysical properties of the absorber, heat transfer fluid, and the heat flux distribution [3]. Distribution of the heat flux on the receiver surface is the only factor which is closely connected with the performance of the heliostat field. Therefore, it can be controlled by defining several aim points and adjusting the heliostats.

Two aiming techniques were described by Kistler [4]. One technique, which is called one-dimensional smart aiming, is to focus the heliostats along the height of the receiver until the spillage loss starts to increase. The heliostats that are closer to the tower are usually focused at the top or the bottom of the receiver while those which are farther are aimed closer to the center of the receiver surface. The two dimensional smart aiming is similar, except the images are distributed in two dimensions. This technique is usually recommended for rectangular cavity apertures or flat plates, as

using other shapes of the receivers may lead to increase in the spillage loss. Although these methods perform well, the technological development of thermal receivers and increasing size of the power plants demand more sophisticated aiming strategies.

In a paper presented by Garcia-Martin et al. [5] an automatic closed-loop control method was developed to optimize the temperature distribution within a volumetric receiver at PSA power plant. The method is based on measuring the temperature at different points on the receiver surface and transferring the power from one area to another by changing the aiming points of the heliostats when the temperature reaches a maximum tolerance value. In another study, Salomé et al. [3] presented an open loop approach to control the flux distribution on the surface of a flat plate receiver. In this method, a set of aiming points are defined and a grid is formed on the surface of the receiver. Then, an optimization algorithm called “TABU+ specific neighborhood” is used to find the best aiming point for each heliostat. The objective is to minimize the flux spread, $F_{max}-F_{min}$, while keeping the spillage loss above a predetermined value. At the first step all heliostats are focused on the center of the receiver. At each iteration, one heliostat is selected and its aiming point is changed. If the modification leads to an improvement in the objective function, it will be saved for the next iteration. It was shown in the paper that the spread of the flux density is decreased by 43% with an added spillage loss of 10% using the proposed algorithm.

Optimization in engineering design has always been a subject of interest to engineers. The genetic algorithm (GA), as one of the

* Corresponding author. Tel.: +1 813 974 0956; fax: +1 813 974 5250.

E-mail address: goswami@usf.edu (D. Yogi Goswami).

Nomenclature

A_m	mirror surface area (m^2)	P_h	total power sent by a heliostat
$\cos w$	cosine factor	P_c	crossover probability
D	distance between the center of the heliostat and the aim point (m)	P_m	mutation probability
d	square root of the heliostat area (m)	P_{mm}	second mutations probability
F	flux density ($\frac{\text{kW}}{\text{m}^2}$)	$\cos rec$	incidence cosine of the reflected central ray from the heliostat on the receiver surface ($^\circ$)
F_{max}	maximum flux density ($\frac{\text{kW}}{\text{m}^2}$)	W_s	image dimension in sagittal plane
F_{min}	minimum flux density ($\frac{\text{kW}}{\text{m}^2}$)	ρ	reflectivity factor
f	focal distance (m)	σ_{HF}	effective deviation (mrad)
f_{at}	atmospheric attenuation factor	σ_{sun}	sunshape error (mrad)
H_t	image dimension in tangential plane	σ_{bq}	beam quality error (mrad)
I_D	direct normal irradiation ($\frac{\text{kW}}{\text{m}^2}$)	σ_{ast}	astigmatic error (mrad)
m	number of heliostats	σ_t	tracking error (mrad)
n	number of aiming points	σ_s	mirror slope error (mrad)

most popular optimization techniques, has been found very useful in solving complex real-world design optimization problems since it works with a population of candidate solutions, not a single point in the search space. This helps to avoid being trapped in local optima as long as the diversity of the population is well preserved [6].

Over the past decade, genetic algorithm has been extensively used for the optimization of solar thermal systems [7]. Varun and Siddhartha used GA to optimize the thermal performance of a flat plate solar air heater [8]. Loomans and Visser applied GA for the optimization of a solar water heater system [9]. Godarzi et al. [10] employed GA to optimize the performance of a solar absorption chiller. GA and artificial neural network were used together by Kalogirou [11] to find the optimum combination of the collector area and storage-tank size for a solar industrial process heat system. Baghernejad and Yaghoubi [12] conducted an exergoeconomic analysis and optimization of a 400 MW integrated solar combined cycle system using GA. Ahmadi et al. [13] investigated multi-objective optimization of a solar dish Stirling engine using GA by considering three objective functions, i.e. output power, overall thermal efficiency, and rate of entropy generation. Cabello et al. [14] developed a program based on GA to find the optimal size of the solar collector area, thermal storage and power of the auxiliary system in a direct steam generation power plant.

In this paper, a new optimization approach based on the principles of GA is proposed to find the optimal flux distribution on the receiver surface of a solar power tower plant. The objective is to minimize the standard deviation of the flux density distribution on the receiver surface by changing the aiming points of individual heliostats. The HFLCAL method [1] is used to find the flux distribution of individual heliostats and is validated against experimental data. After presenting the optimization methodology, the final results are provided and the influences of different parameters are investigated.

2. Flux density model

The flux density on the surface of a receiver can be found numerically or analytically. In the numerical approach, called Monte Carlo ray tracing method, a large number of rays are generated and traced through different optical stages. A flux map on the receiver surface can be generated from the intersection of the reflected rays and the surface. SolTrace software [15], developed by the National Renewable Energy Laboratory (NREL), can be used to predict the flux density distribution on the receiver surface

accurately using the Monte Carlo ray tracing method. Although the numerical method is very accurate, it requires large computational time.

Two well-known analytic models that are used to evaluate the flux density and interception efficiency are the UNIZAR model from the Universidad de Zaragoza [16] and the HFLCAL model from DLR (the German Aerospace Center) [1]. According to [17], both of these models are appropriate tools though HFLCAL is simpler and slightly more accurate than UNIZAR. The HFLCAL model is used in this study to evaluate the flux density distribution of each heliostat on the receiver surface. The flux map resulting from the entire field is generated by superimposing the flux densities of the individual heliostats.

2.1. HFLCAL Model

In the HFLCAL model a circular normal distribution is used to find the flux density distribution on the receiver surface, given as [3]:

$$F(x, y) = \frac{P_h}{2\pi\sigma_{HF}^2} \exp\left(-\frac{(x-x_t)^2 + (y-y_t)^2}{2\sigma_{HF}^2}\right) \quad (1)$$

where P_h is the total power reflected by a heliostat, σ_{HF} is the effective deviation, and (x_t, y_t) are the coordinates of the aiming point on the receiver surface. P_h is given as:

$$P_h = I_D \cdot A_m \cdot \cos w \cdot f_{at} \cdot \rho \quad (2)$$

where I_D is the direct normal irradiation ($\frac{\text{kW}}{\text{m}^2}$), A_m is the mirror area, $\cos w$ is the cosine factor of the angle between the sun ray and the normal to the heliostat surface, f_{at} is the atmospheric attenuation factor, and ρ is the reflectivity of the heliostat.

The effective deviation, σ_{HF} , is the result of the convolution of the four Gaussian error functions, namely, the sun shape error due to the non-uniform distribution of the solar intensity across the sun disk (σ_{sun}), the beam quality error due to the mirror slope error (σ_{bq}), the astigmatic error representing any extra deformation of the reflected ray if the incident ray is not parallel to the mirror's normal (σ_{ast}), and the tracking error (σ_t). σ_{HF} is given as [17]:

$$\sigma_{HF} = \frac{\sqrt{D^2(\sigma_{sun}^2 + \sigma_{bq}^2 + \sigma_{ast}^2 + \sigma_t^2)}}{\sqrt{\cos rec}} \quad (3)$$

where D is the distance between the center of the heliostat and the aim point, and $\cos rec$ represents the cosine of the angle between

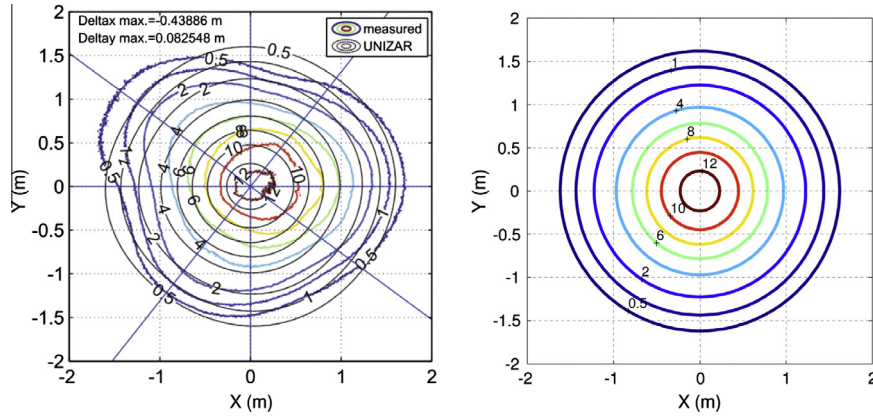


Fig. 1. Contours of flux densities for a heliostat in the PSA power plant: (left) measured and calculated values using the UNIZAR model [17]. (Right) calculated values using the HFLCAL model.

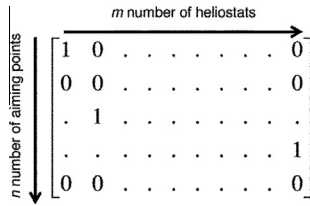


Fig. 2. A sample form of a candidate solution.

the reflected ray and the normal to the receiver surface. The beam quality error is due to imperfections of the heliostat surface and is related to the slope error by:

$$\sigma_{bq} = (2\sigma_s)^2 \quad (4)$$

The standard deviation of the astigmatic error is given as:

$$\sigma_{ast} = \frac{\sqrt{0.5(H_t^2 + W_s^2)}}{4D} \quad (5)$$

where H_t and W_s are the image dimensions in the tangential and sagittal plane [18] and are given as:

$$H_t = d \left| \frac{D}{f} - \cos w \right| \quad (6)$$

$$W_s = d \left| \frac{D}{f} \cos w - 1 \right| \quad (7)$$

In the above equations, f represents the focal distance and d is a general dimension of the heliostat. In this study, d is equal to the square root of the heliostat area.

The interception efficiency, defined as the fraction of the reflected power that reaches the receiver surface at a certain point in time, is calculated by [1]:

$$\eta_{int} = \frac{1}{2\pi\sigma_{HF}^2} \int_x \int_y \exp\left(-\frac{(x-x_t)^2 + (y-y_t)^2}{2\sigma_{HF}^2}\right) dx dy \quad (8)$$

A model is developed in MATLAB based on the HFLCAL method to calculate the flux density at the receiver of a solar power tower plant. The model is validated against the experimental data available from the PSA power plant [17]. Each heliostat used in the experimental study was 6.6778 m wide and 6.819 m high and contained 12 spherical facets (1.105×3.010 m). However, all the

heliostats were modeled as single mirrors in the simulation. The total mirror area of each heliostat was 39.9126 m^2 . The information about each heliostat including the coordinates, actual distance to the receiver plane, and the focal length are given in [17]. It is assumed that the direct normal irradiation is 1 kW/m^2 , the mirrors are perfect reflectors, and atmospheric attenuation is negligible. Therefore, the total power reflected by each heliostat using Eq. (2) is given as:

$$P_h = 39.9126 \times \cos w \text{ (kW)} \quad (9)$$

Using Eq. (1) and the information given in [17], the flux densities for the heliostats are obtained. Fig. 1 depicts the contours of flux densities for one of the heliostats. The left figure shows the measured as well as the simulated values using the UNIZAR model. The right figure depicts the flux density distribution obtained from the HFLCAL method. As can be clearly seen, analytical methods are not able to exactly predict the real shapes of the flux density contours due to the circular symmetry assumption, however, they are able to predict accurately the flux density levels on the receiver surface. By comparing the two figures, it can be concluded that the HFLCAL method works very well and can be confidently used.

3. Optimization algorithm

An optimization algorithm is developed based on the principles of GA. GA belongs to the larger class of evolutionary algorithms that mimic the process of natural evolution in order to find the best solution to an optimization problem [19]. The genetic operators such as mutation and crossover are applied to a population of

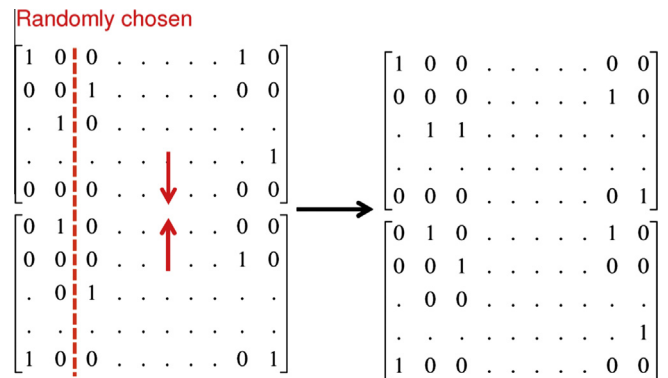


Fig. 3. Crossover operation on two of the candidate solutions.

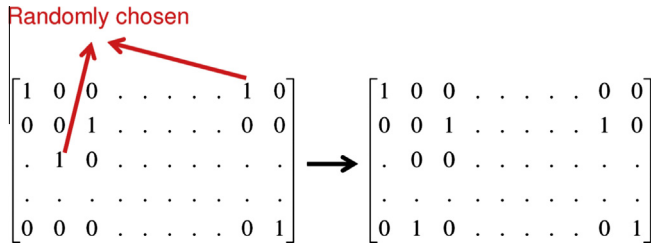


Fig. 4. Mutation operation on one of the candidate solutions.

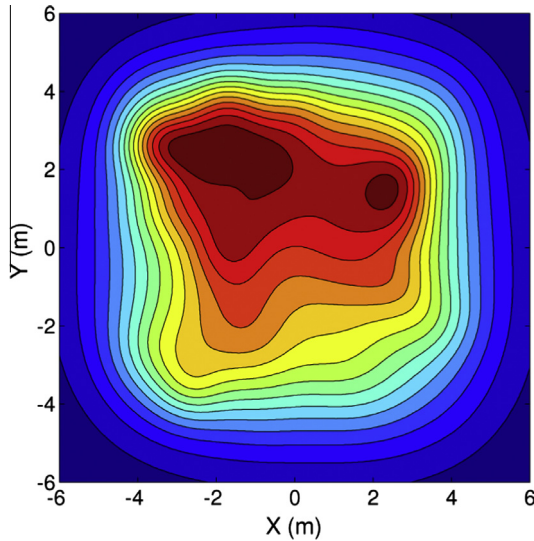


Fig. 5. Flux density map for a randomly generated binary matrix.

candidates. The best candidates are selected at the end of each generation by measuring the fitness function. The process is repeated for a number of generations until the best solution is found. The optimization algorithm can be summarized as:

- (1) Initial population is randomly generated.
- (2) The fitness function is evaluated for each population.
- (3) The offsprings are generated by applying genetic operators, i.e. crossover and mutation, to probabilistically selected individuals from the initial population.
- (4) The fitness function is evaluated for the offsprings.
- (5) New population is selected and the algorithm continues from step 2.

In this paper, the genetic algorithm is employed to find an aiming strategy for a solar power tower plant in order to distribute the flux uniformly on the receiver surface. The main objective is to minimize the standard deviation of the flux density distribution, which is found by measuring the flux density at multiple points on the receiver surface. The detailed methodology is explained in subsequent sections.

3.1. Generating initial population

In the GA, each candidate is usually represented as a vector containing information about all the design variables. In this problem, each candidate is represented by a matrix where the numbers of columns and rows are equal to the numbers of heliostats and aiming points, respectively. Therefore, for n number of aiming points and m number of heliostats, the size of the matrix will be $n \times m$,

as shown in Fig. 2. The heliostats are numbered from 1 to m . Similarly, the aiming points are numbered from 1 to n . The matrix shown in Fig. 2 indicates that the first heliostat is focused on the first aiming point; the second heliostat is focused on the third aiming point; and the m th heliostat is focused on the $(n - 1)$ th aiming point.

The number of matrices that are randomly generated in this step, called the number of initial population, is defined by the user. A MATLAB cell data structure is used for the programming [20].

3.2. Crossover operator

In the crossover process two of the candidate solutions are selected and combined to produce children, which are the new candidate solutions. The crossover probability (P_c) is the parameter that controls how often the crossover will be performed, which is defined by the user [19]. The crossover process consists of three main steps as shown in Fig. 3:

- (1) Two of the candidate solutions are randomly selected.
- (2) A column number is randomly selected.
- (3) The values are swapped between the two matrices following the selected column number.

The main intention of using crossover is to find new solutions that contain good parts of the old solutions; however, it does not necessarily mean that the offsprings are any better than the parents.

3.3. Mutation operator

Mutation is another genetic operator which helps to avoid being trapped in the local minimum and maintains the diversity in the population [20]. Similar to crossover probability, mutation probability (P_m) controls how often the mutation is performed on the old population. The mutation is incorporated into the program by the following steps:

- (1) A candidate solution from the old population is randomly selected.
- (2) One of the columns of the chosen matrix is selected. The element in that column that is equal to 1 is changed to 0.
- (3) Another element of that column is randomly selected and is changed from 0 to 1.

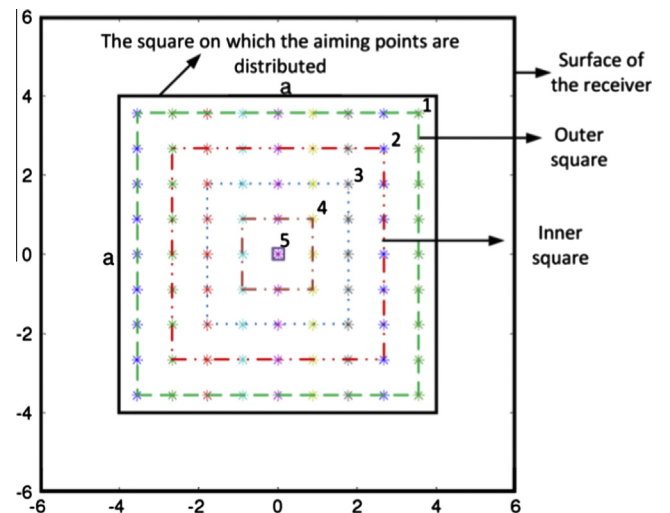


Fig. 6. The receiver surface, aiming surface, and the generated squares that are used to explain the algorithm.

Considering the physics of the problem, it is expected that performing mutation only on one column will not change the objective function very much. In other words, changing the aiming point of a single heliostat will not affect the overall standard deviation of the flux density distribution significantly. Therefore, the program is written in a way that allows mutation to be performed on multiple columns of the selected matrix. The number of mutations is defined by the second mutation probability (P_{mm}). In other words, for each column a random number is generated and mutation will be performed on that column if the random number is less than P_{mm} .

Fig. 4 depicts the mutation operation on a randomly selected matrix. As it can be seen, mutation is performed on the second and $(m - 1)$ th columns, which means that the aiming points of the second and $(m - 1)$ th heliostat are changed.

3.4. Selection

The last step is to select the best candidates from the old population and the offsprings for the next generation. Tournament selection strategy is used for this purpose which involves running several tournaments between two randomly chosen candidates.

The winner of each tournament is the one with the lowest standard deviation of the flux density distribution on the receiver surface. The tournament competitions continue until the number of the selected candidates equals the number of in initial population. One generation is completed by selecting the new population and the program proceeds to the next generation. The program continues to run until the maximum number of generations defined by the user is reached or some other termination criterion is met.

3.5. Self-modifying algorithm

As it is already discussed, the optimization algorithm is based on generating random binary matrices. The flux density maps produced by these random matrices do not usually reflect the expected shapes. In other words, the maximum flux density might be located at the corner of the receiver or the contours may not follow a reasonable pattern. This problem is clearly shown in Fig. 5. Therefore, another algorithm, called self-modifying algorithm, needs to be developed to modify the flux density maps and turn them into more realistic shapes by changing the elements of the random matrices. In this program the ideal map is defined as the one in which the maximum flux density is located as close as

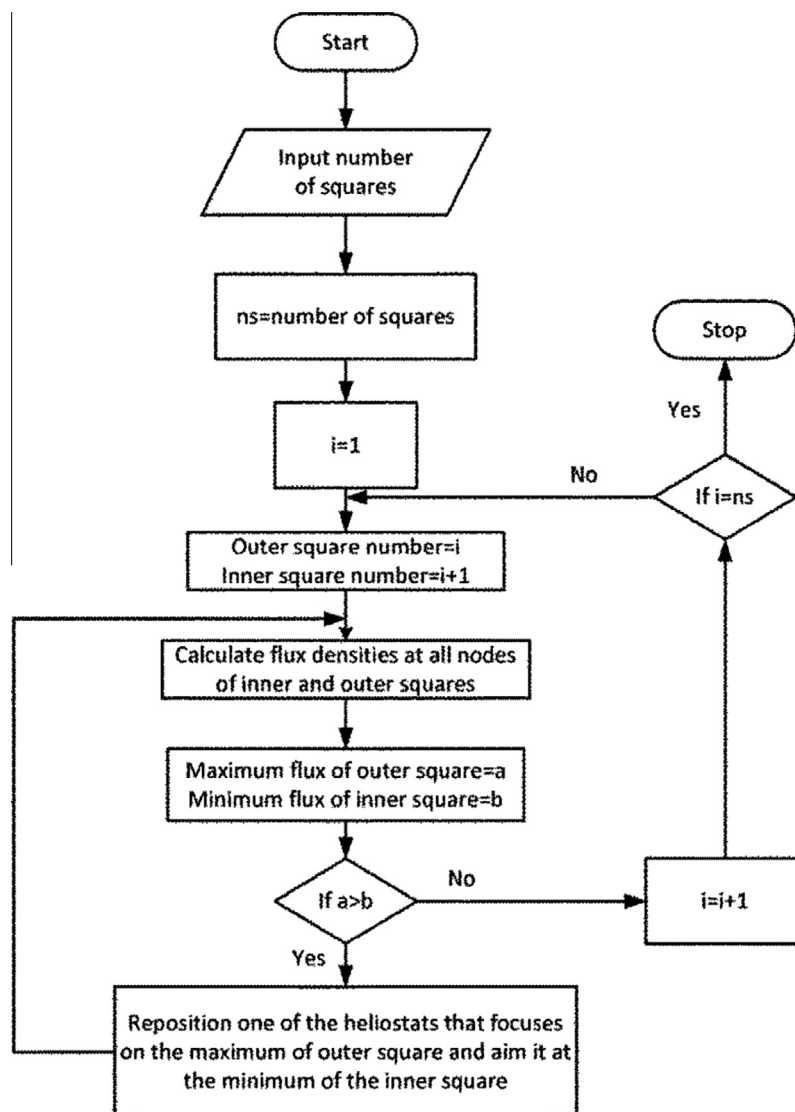


Fig. 7. Flowchart for the self-modifying algorithm.

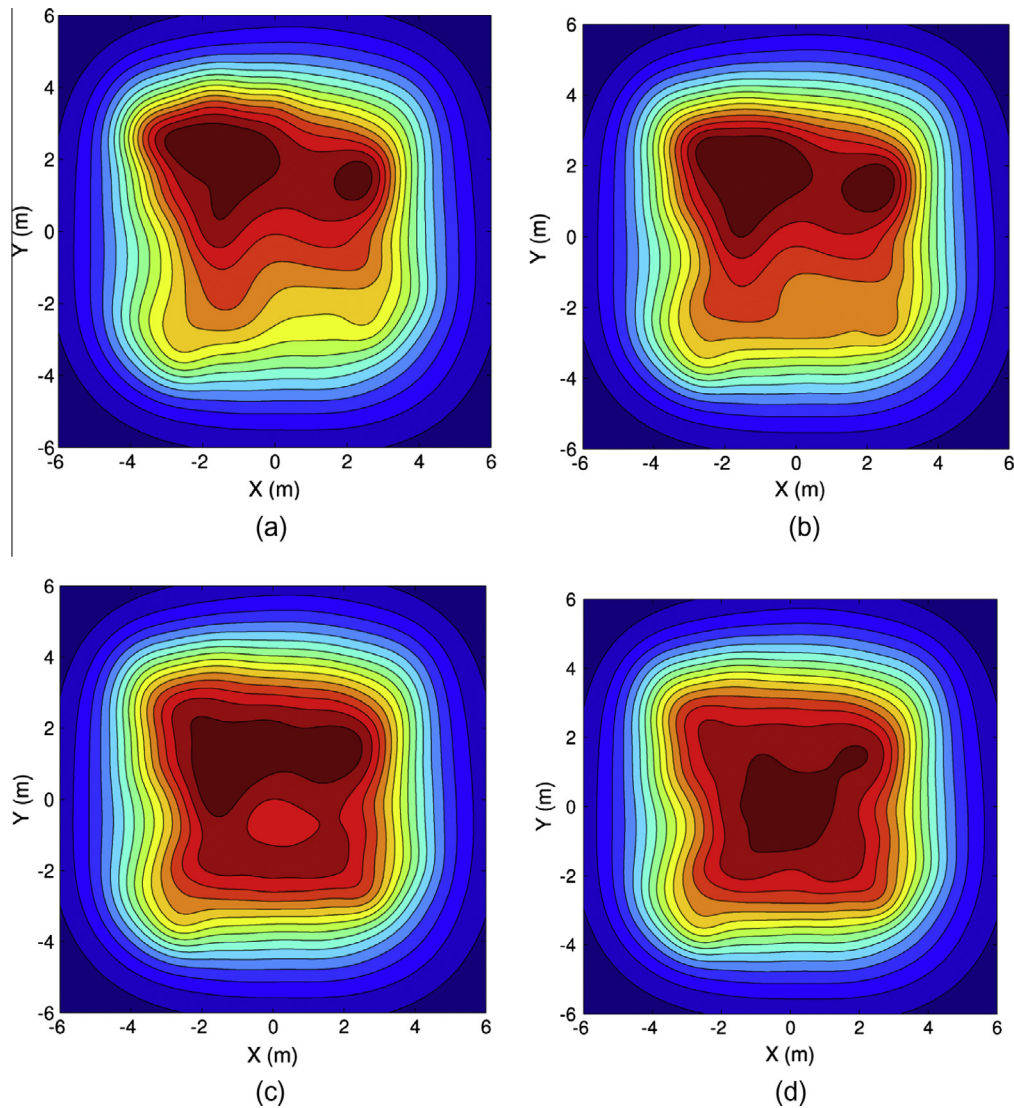


Fig. 8. Modification of flux density map shown in Fig. 5 by changing the aiming points of the heliostats (a) 3rd iteration, (b) 8th iteration, (c) 16th iteration, (d) 24th and the last iteration.

possible to the center of the receiver and gradually decreases as it gets closer to the receiver sides.

The algorithm developed to handle this task can be explained with the aid of Fig. 6. The largest square represents the receiver surface and 81 aiming points are distributed on a smaller square, which is called aiming surface.

The discussion about the size of this surface and the number of aiming points is presented later. As shown in Fig. 6, the aiming points can be connected to each other to form new squares. Beginning from the squares #1 and #2 as the outer and inner squares, respectively, the flux densities for all the aiming points located on the sides are calculated. The maximum flux on the square #1 should be less than the minimum flux on the square #2. If this constraint is violated, one of the heliostats that are focused on the aiming point representing the maximum of square #1 is repositioned and is focused on the point having the minimum flux density of square #2. This algorithm continues until the flux density at all the points on square #1 becomes less than those on square #2. Next, the outer square is replaced by square #2 and the inner square is represented by square #3 and the process continues. The flowchart for the algorithm is shown in Fig. 7.

During optimization, all the generated matrices are self-modified by this algorithm. The algorithm is applied to the flux map shown in

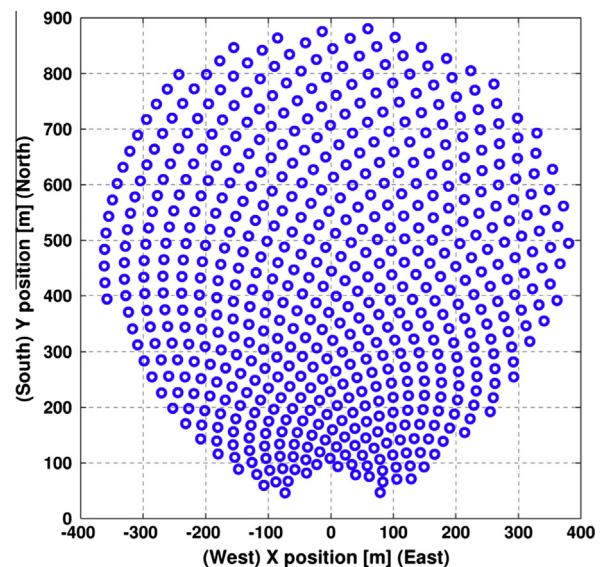


Fig. 9. Heliostat field for a 50 MWth solar power tower plant in Daggett, California.

Table 1
Field parameters.

<i>Heliostats</i>	
Width	12.84 m
Height	9.45 m
Reflectivity	0.88
<i>Receiver</i>	
Tower height	115 m
Tilt angle of the aperture	12.5°
Aperture width	12 m
Aperture height	12 m

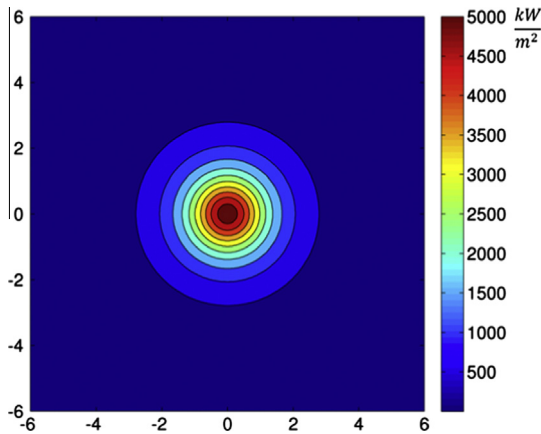


Fig. 10. Flux density map for the solar power tower plant assuming all the heliostats aim at the center of the receiver.

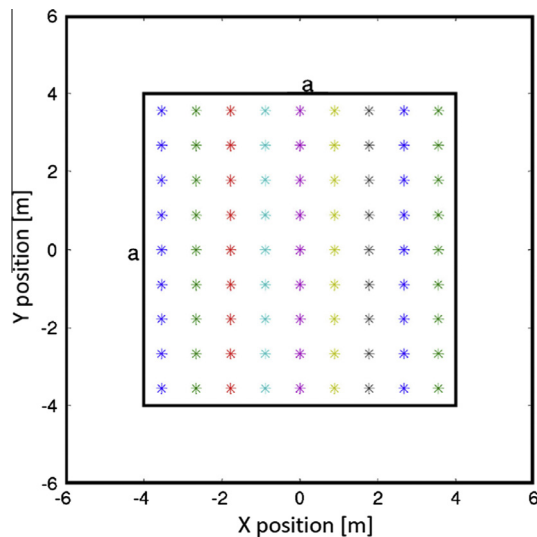


Fig. 11. Distribution of the aiming points on the receiver surface.

Fig. 5. Fig. 8 depicts how the flux density map is modified with the number of iterations. As can be seen, on the 24th iteration the maximum flux density is located at the center and gradually decreases until it reaches the minimum level close to the sides of the receiver.

4. Results and discussion

4.1. Optimization results

As a case study, a field layout as shown in Fig. 9 was designed for a 50 MWth system in Daggett, California. There are 580 helio-

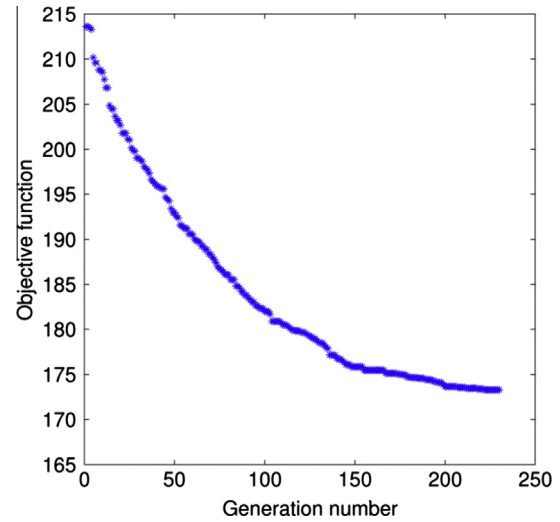


Fig. 12. Variation of the objective function with the generation number.

stats which are placed on the field based on the biomimetic layout proposed by Noone et al. [21]. This field and the methods explained in the preceding sections are employed to find the optimal flux density distribution on the receiver surface. Other field parameters are given in Table 1. It is assumed that σ_{sun} is 2.51×10^{-3} mrad, σ_s is 10^{-3} mrad, the tracking error is negligible, and the facet canting is on-axis parabolic.

On March 21st at noon, the direct normal radiation in Daggett is given as $0.926 \frac{kW}{m^2}$ [22]. Assuming all the heliostats aim at the center of the receiver at this time of the year, the flux density map using the HFLCAL method is shown in Fig. 10. As can be seen, the flux density at the center of the receiver is close to $5000 \frac{kW}{m^2}$, which is extremely high. Therefore, an aiming strategy is required to uniformly distribute the flux over the entire surface.

In this regard, a number of aiming points are distributed on the receiver surface, as shown in Fig. 11. All of these points are located inside a square which is called the aiming surface. Then, the optimization algorithm is used to find the appropriate aiming point for each heliostat that leads to the least standard deviation of the flux density distribution on the entire surface. In this study, the aiming surface is a 8×8 square on which 81 aiming points are uniformly distributed. The evolutionary process of optimization is accomplished with a population size of 100 with crossover probability, P_c , mutation probability, P_m , and second mutation probability, P_{mm} , of 0.9, 0.2, and 0.5 respectively. Fig. 12 shows the variations of the objective function with the generation number. The optimization algorithm is terminated after 235 generations when the objective function reaches a plateau.

Fig. 13 depicts the optimal flux distribution on the receiver surface. It can be seen that the maximum flux density is $550 \frac{kW}{m^2}$, which is almost one tenth of the maximum flux when all the heliostats aim at the center of the receiver (Fig. 10). Therefore, it can be concluded that the new algorithm is able to successfully distribute the flux on the entire surface. The interception efficiency using the proposed aiming strategy is 0.9214 as opposed to 0.9906 in the original case. According to Fig. 13, there is a spot which is shown as dark red and is not located at the center of the surface. The reason is that the self-modifying algorithm is based on calculating and comparing the flux densities only at the aiming points. Therefore, there might be some points in between that cannot be captured by the algorithm. This is not a concern as long as the size of the spot is small. However, increasing the number of the aiming points can fix this problem, which is discussed in the following sections.

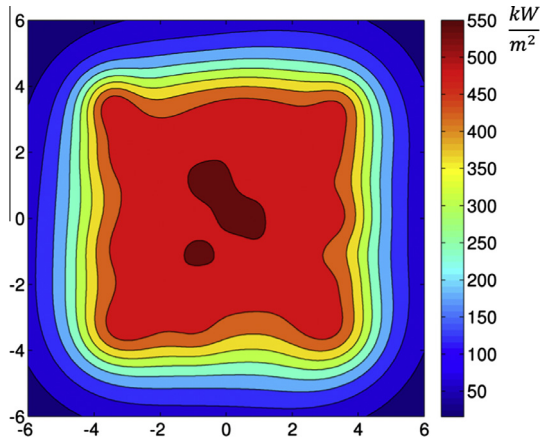


Fig. 13. Optimal flux density distribution on the receiver surface.

A map of the heliostat field is presented in Fig. 14 to show which heliostats were aimed at which points. The numbering for the aiming points begins from the bottom left corner in Fig. 11 and ends at the top right.

4.2. Influence of the aiming surface size

The size of the aiming surface is an important parameter which directly affects the flux density distribution as well as the interception efficiency. A smaller aiming surface leads to higher interception efficiency and higher maximum flux density, and vice versa. Fig. 15 shows the variations of the interception efficiency and the maximum flux density with respect to the size of the aiming surface. In this case, the aiming surface is represented by a square on which 81 aiming points are distributed. The calculations were performed for March 21st for Daggett, California.

As can be clearly seen in Fig. 15, the smallest size of the aiming surface (5 m × 5 m) has the highest interception efficiency and the

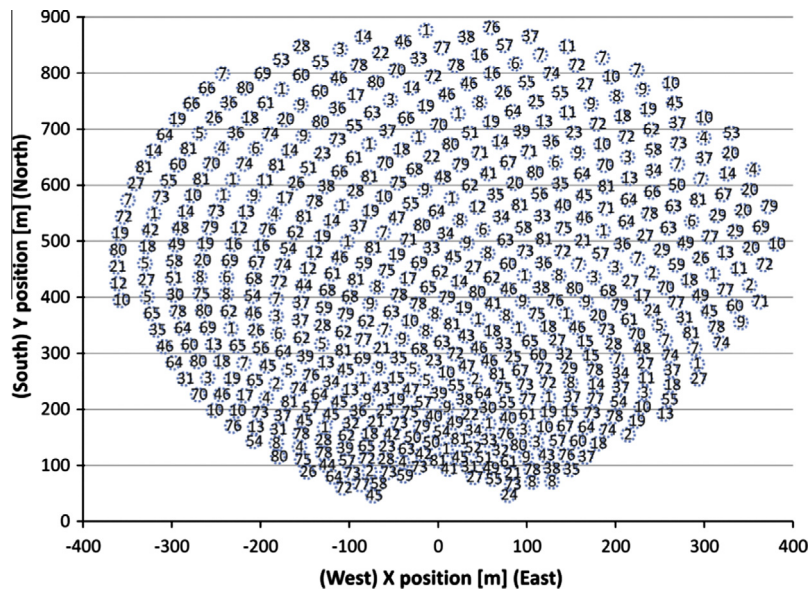


Fig. 14. A map of the heliostat field showing which heliostat were aimed at which point.

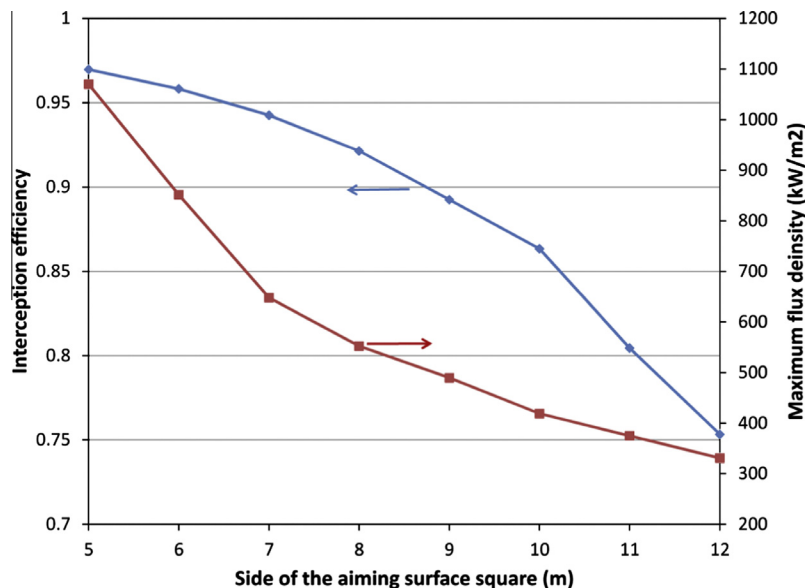


Fig. 15. Variations of interception efficiency and maximum flux density with the size of the aiming surface.

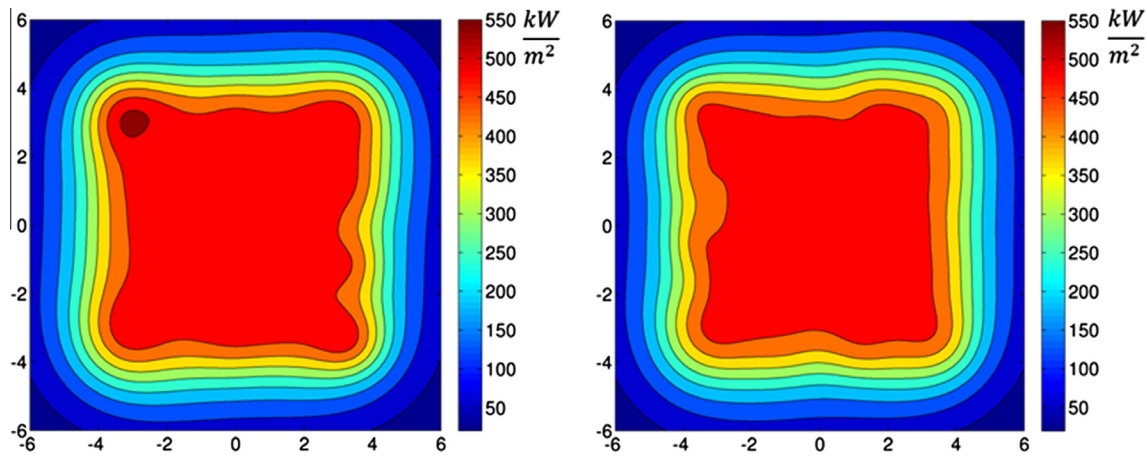


Fig. 16. Optimal flux density distribution on the receiver surface: (left) 49 aiming points (right) 121 aiming points.

maximum flux density increases to 1070 kW/m^2 . As the size of the aiming surface increases to $12 \text{ m} \times 12 \text{ m}$, the interception efficiency decreases to 0.7533. This means that close to 25% of the energy reflected by the heliostats is lost and not intercepted by the receiver. This has a huge impact on the performance of the power plant.

Therefore, one has to consider the maximum heat flux density that can be tolerated by the receiver surface and size the aiming surface accordingly. It is noteworthy that by decreasing the size of the aiming surface, it might be necessary to decrease the number of aiming points as distributing a large number of aiming points on a small surface can be a challenge from practical point of view.

4.3. Influence of the number of aiming points

Increasing the number of aiming points leads to better distribution of the heat flux on the receiver surface. Moreover, the self-modifying algorithm is more efficient when a large number of aiming points is employed. However, in a real power plant the number of aiming points that can be distributed on a surface depends on the size of the surface and uncertainty in aiming the heliostats. Therefore, having a very large number of aiming points on a small receiver may not be practical nor necessary.

Fig. 16 depicts the flux maps on the receiver surface when 49 and 121 aiming points are considered. All other parameters are same as those used in Fig. 13. As can be clearly seen from the left plot, when there are 49 aiming points, the maximum flux density is located on the left corner of the square. However, the size of this spot is small and the flux density on this point is not very different from its neighbors. Moreover, the flux density is well-distributed over the entire surface of the receiver. Therefore, it can be concluded that although the number of aiming points has decreased from 81 to 49, the algorithm is still able to distribute the flux very efficiently. The same analysis is carried out for 121 aiming points and the resulting flux map is shown on the right plot. According to the figure, there is no dark spot and the flux density is perfectly distributed on the surface and the maximum flux density is about $500 \frac{\text{kW}}{\text{m}^2}$.

From the results shown in this section, it can be concluded that it is desirable to have a larger number of aiming points from computational point view, even though the program is still able to distribute the flux efficiently using a smaller number of aiming points. The selection of the number of aiming points depends on the size of the receiver and uncertainties in aiming the heliostat.

5. Conclusions

The work in this paper presents an optimization algorithm that can be used to obtain uniform heat flux density distribution on the receiver surface of a solar power tower plant. The flux density of individual heliostats was modeled using the HFLCAL method, which was validated against experimental data. The optimization code was developed based on the principles of GA and modified by considering the physics of the problem. The results showed that using the new algorithm the maximum flux density is reduced by a factor of 10, reaching around $500 \frac{\text{kW}}{\text{m}^2}$. The analysis has shown that the size of the aiming surface has a huge impact on the interception efficiency and the maximum flux density and should be chosen as small as possible. This, of course, depends on the maximum flux density that the receiver material can tolerate. Moreover, it is shown that the algorithm works very well for different numbers of aiming points, however, it is desirable to increase this number as much as possible. It is noteworthy that in this paper the heliostats are modeled as single mirrors, but the algorithm would also be applicable if the heliostats were represented by different facets.

References

- [1] Schwarzbözl P, Schmitz M, Pitz-paal R. Visual HFLCAL – a software tool for layout and optimization of heliostat fields. Berlin: SolarPACES; 2009.
- [2] Winter C, Sizmann R, Vant-Hull L. Solar power plants. Berlin: Springer; 1991.
- [3] Salomé A, Chhel F, Flamant G, Ferrière A, Thiery F. Control of the flux distribution on a solar tower receiver using an optimized aiming point strategy: application to THEMIS solar tower. Sol Energy 2013.
- [4] Kistler BL. A User's manual for DELSOL3: a computer code for calculating the optical performance and optimal system design for solar thermal central receiver plants. Sandia National Labs, Albuquerque, NM. SAND86-8018; 1986.
- [5] García-Martín FJ, Berenguel M, Valverde A, Camacho EF. Heuristic knowledge-based heliostat field control for the optimization of the temperature distribution in a volumetric receiver. Sol Energy 1999;66:355–69.
- [6] Renner G, Ekárt A. Genetic algorithms in computer aided design. Comput-Aided Des 2003;35:709–26.
- [7] Sharma N, Varun, Siddhartha. Stochastic techniques used for optimization in solar systems: a review. Renew Sustain Energy Rev 2012;16:1399–411.
- [8] Varun, Siddhartha. Thermal performance optimization of a flat plate solar air heater using genetic algorithm. Appl Energy 2010;87:1793–9.
- [9] Loomans M, Visser H. Application of the genetic algorithm for optimization of large solar hot water systems. Sol Energy 2002;72:427–39.
- [10] Godarzi AA, Jalilian M, Samimi J, Jokar A, Vesaghi MA. Design of a PCM storage system for a solar absorption chiller based on exergoeconomic analysis and genetic algorithm. Int J Refrig 2013;36:88–101.
- [11] Kalogirou SA. Optimization of solar systems using artificial neural-networks and genetic algorithms. Appl Energy 2004;77:383–405.
- [12] Baghernejad A, Yaghoubi M. Exergoeconomic analysis and optimization of an Integrated Solar Combined Cycle System (ISCCS) using genetic algorithm. Energy Convers Manage 2011;52:2193–203.

- [13] Ahmadi MH, Mohammadi AH, Dehghani S, Barranco-Jiménez MA. Multi-objective thermodynamic-based optimization of output power of solar dish-Stirling engine by implementing an evolutionary algorithm. *Energy Convers Manage* 2013;75:438–45.
- [14] Cabello JM, Cejudo JM, Luque M, Ruiz F, Deb K, Tewari R. Optimization of the size of a solar thermal electricity plant by means of genetic algorithms. *Renew Energy* 2011;36:3146–53.
- [15] Wendelin T. SOLTRACE a new optical modeling tool for concentrating solar optics. In: *Proc. ISEC, Hawaii*, 2003.
- [16] Collado FJ, Gomez A, Turegano JA. An analytic function for the flux density due to sunlight reflected from a heliostat. *Sol. Energy* 1986;37:215–34.
- [17] Collado FJ. One-point fitting of the flux density produced by a heliostat. *Sol. Energy* 2010;84:673–84.
- [18] Igel EA, Hughes RL, Laboratories S. Optical analysis of solar facility heliostats. *Sol. Energy* 1979;22:283–95.
- [19] Sivanandam SN, Deepa SN. *Introduction to genetic algorithms*. Springer; 2007.
- [20] MATLAB. The MathWorks Inc.; 2012.
- [21] Noone CJ, Manuel T, Mitsos A. Heliostat field optimization A new computationally efficient model and biomimetic layout. *Sol. Energy* 2012;86:792–803.
- [22] ASHRAE Handbook of Fundamentals. American Society of Heating, Refrigerating and Air Conditioning Engineers, Atlanta, Georgia, 2013. p. 14.9 [chapter 14].